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ANFIS Models with Subtractive Clustering and Fuzzy C-Mean Clustering Techniques for Predicting Swelling Percentage of Expansive Soils

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ABSTRACT

Civil engineering faces significant challenges from expansive soils, which can lead to structural damage. This study aims to optimize subtractive clustering and Fuzzy C-Mean Clustering (FCM) models for the most accurate prediction of swelling percentage in expansive soils. Two ANFIS models were developed, namely the FIS1S model using subtractive clustering and the FIS2S model utilizing the FCM algorithm. Due to the MATLAB graphical user interface's limitation on the number of membership functions, the coding approach was employed to develop the ANFIS models for optimal prediction accuracy and problem-solving time. So, two programs were created to determine the optimal influence radius for the FIS1S model and the number of membership functions for the FIS2S model to achieve the highest prediction accuracy. The ANFIS models have demonstrated their highest predictive ability in predicting swelling percentage, thanks to the optimization of membership functions and cluster centers. The developed programs also showed excellent performance and can be potentially applied to optimize subtractive clustering and FCM models in accurately modeling various engineering aspects.

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1. Introduction

Expansive soils are characterized by changes in their volume due to variations in their water content. These changes are often related to seasonal changes, such as rainfall and vegetation evapo-transpiration, as well as to other factors such as leakage from water supply pipes or sewage from water storage tanks, changes in groundwater levels, and the planting, removal, or severe pruning of trees or hedges. Expansive soils are commonly found in arid and semi-arid regions across the globe [1]. The swelling of these soils can lead to damage to various structures [2], especially low-height and lightweight buildings, pavements, highways, retaining walls, airports, sidewalks, canal beds, and tunnels . Repairing damages caused by expansive soils to structures incurs significant costs, with an estimated $300 million in the UK, $1 billion in the USA per year, and many billions of dollars worldwide. Consequently, researchers have been investigating the appropriate methods for predicting soil expansion to mitigate expected structural damage [2].

To ensure a suitable, safe, and cost-effective design of structural foundations on expansive soils, it is crucial to determine their swelling percentage. However, measuring this feature in geotechnical laboratories can be both time-consuming and expensive. To mitigate the cost and time required for swelling tests, researchers have developed empirical relations to predict swelling in expansive soils during the pre-design stage. These relations provide quick estimates of swelling, which can be used for the initial design of foundations for structures built on expansive soils. They can also be used to verify data collected from laboratory and field tests. Therefore, the use of more powerful techniques with higher prediction abilities is essential in geotechnical engineering [3].

In recent times, there has been progress in the application of Artificial Intelligence (AI) methods such as Adaptive Neuro Fuzzy Inference Systems (ANFIS), Support Vector Machine (SVM), Genetic Program (GP), and Artificial Neural Networks (ANNs) within the field of civil engineering [3–18] and geotechnical numerical modeling [19–22]. The use of AI methods in geotechnical engineering has also been on the rise. Kayadelen et al. [23] conducted a study in this field where they employed ANFIS to predict the swelling of compacted soils. The researchers utilized coarse-grained fraction ratio (CG), fine-grained fraction ratio (FG), plasticity index (PI), and maximum dry density (MDD) as inputs for their model.

Yilmaz and Kaynar [24] employed ANFIS to predict the swell percentage (S%) of soils. In their model, the researchers used three soil indices, namely liquid limit, activity, and cation exchange capacity, as inputs. Various parameters, such as initial water content, clay mineral type, initial dry density, clay content, and Atterberg limits, are known to influence the swelling of soils [25].

In previous studies, ANFIS prediction models were commonly developed using MATLAB Graphical User Interfaces (GUIs). However, these GUIs impose a constraint on the maximum number of membership functions, limiting their effectiveness to a maximum of 15 membership functions. To overcome this limitation, our study focuses on constructing fuzzy models with an optimal number of membership functions, employing coding within the MATLAB v 2018 software. This approach aims to achieve the highest level of accuracy and minimize problem-

solving time. In the first stage, two ANFIS models were developed using subtractive clustering and Fuzzy C-Mean Clustering (FCM) algorithms to predict soil swelling. Subsequently, two MATLAB programs were designed to optimize the subtractive clustering and FCM ANFIS models for increased prediction accuracy. Furthermore, sensitivity analysis, utilizing the Cosine Amplitude Method, was conducted to evaluate the influence of inputs on the output for each ANFIS model. However, a thorough literature review and detailed analysis of existing models and their limitations could be beneficial in further justifying the need for the proposed ANFIS models.

2. Materials and methods

2.1. Fuzzy inference systems (FIS)

There are two types of logic: classical and fuzzy logic. Classical logic assigns a membership value of 1 to a member if it belongs to a set, and 0 if it does not belong [26]. However, in fuzzy logic, the membership value for a member can range between 0 and 1. The concept of fuzzy sets was introduced by Zadeh,[11]. The mathematical foundation of a fuzzy set is as follows:

$$A = \{ (x, \mu A(x)) \mid x \epsilon X \} \quad (1)$$

where A is fuzzy set, X is a set of objects denoted generically by x and μA(x) is membership function (MF). For each member, the membership degree in the set, defined by membership function. The degree of membership determines the belonging level of the member to a set.

A Fuzzy Inference System (FIS) is a nonlinear mapping that maps from an input space to an output space using a set of fuzzy if-then rules [27,28]. A fuzzy if-then rule can be expressed as follows:

$$if \quad x \; is \; A \quad then \quad y \; is \; B \quad (2)$$

where A and B are linguistic values defined by fuzzy sets on the ranges (universes of discourses X and Y, respectively). "x is A" is known as antecedent or premise and "y is B" as consequent or conclusion [27].

In general, there are three types of Fuzzy Inference Systems (FIS): Mamdani, Takagi-Sugeno-Kang (also known as the Sugeno model) and Tsukamoto fuzzy models [4,29,30]. The three models have similar antecedent parts, but their consequent parts differ from each other. The Mamdani and Tsukamoto fuzzy models have membership functions in their consequent parts, while the consequent part of Sugeno fuzzy models consists of a linear equation in the first order and a fixed value in the zero order Sugeno model. The steps involved in constructing a fuzzy inference system can generally be described as follows:

1) Determine the fuzzy inference system.
2) Fuzzify the antecedent and consequent using fuzzy membership functions.
3) Combine different antecedent parts in the rules and assess their impact on the final output.
4) Combine the consequent parts of the rules to obtain the best final output in the form of a fuzzy set.

5) If necessary, convert the final output to a classical number using defuzzification methods.

2.2. Adaptive neuro-fuzzy inference system (ANFIS)

The concept of the Adaptive Neuro-Fuzzy Inference System (ANFIS) was pioneered by Jang [31], melding the strengths of neural networks and fuzzy inference systems. ANFIS leverages neural networks' learning abilities alongside fuzzy inference systems' descriptive capacities to establish a mapping between input and output spaces. When provided with input-output data, ANFIS can construct a Sugeno Fuzzy Inference System [32]. For instance, in a scenario with two inputs, x and y, and one output, F, a Sugeno FIS might be articulated using two rules [33]:

$$Rule\ 1: \quad if \quad x\ is\ A_1 \quad , \quad y\ is\ B_1 \quad then \quad f_1 = p_1 x + q_1 y + r_1 \tag{3}$$

$$Rule\ 2: \quad if \quad x\ is\ A_2 \quad , \quad y\ is\ B_2 \quad then \quad f_2 = p_2 x + q_2 y + r_2 \tag{4}$$

where A_i and B_i are the linguistic labels of i^{th} rule and p_i, q_i and r_i are the consequent parameters of a Sugeno FIS as shown in Fig 1.

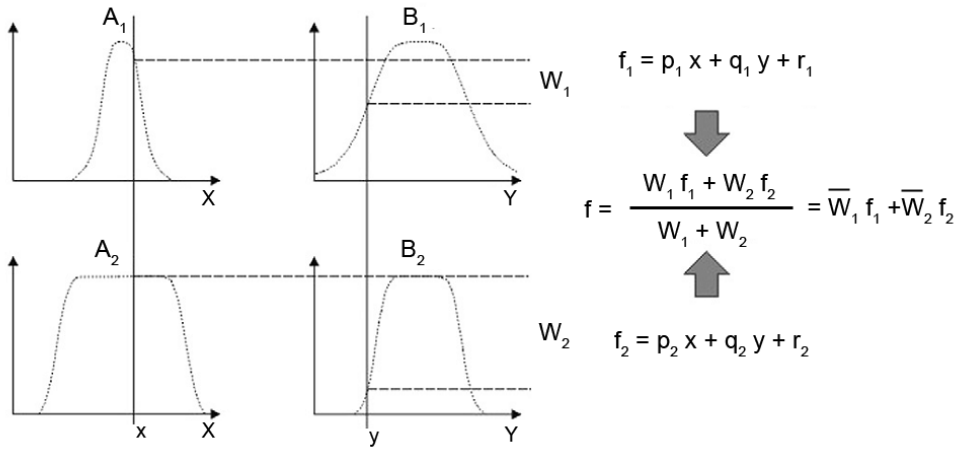

Fig. 1. Description of Sugeno fuzzy model [11].

ANFIS is a sophisticated system capable of autonomously training and fine-tuning the fuzzy system's parameters. It utilizes a unique hybrid learning algorithm that merges the principles of gradient descent and least-squares methods. In this algorithm, the gradient descent component is employed to enhance the premise parameters responsible for shaping the membership functions, whereas the least-squares method is applied to refine the consequent parameters, such as the p_i, q_i, and r_i coefficients in the Sugeno FIS model. As the hybrid learning algorithm progresses through its forward pass, node outputs advance forward, enabling the identification of consequent parameters using the least-squares method. Subsequently, during the backward pass, error signals propagate in the opposite direction, facilitating the adjustment of premise parameters via gradient descent [4]. Table 1 succinctly outlines the tasks undertaken in each stage. Notably, the optimization of consequent parameters occurs while maintaining the premise parameters constant. The key benefit of this hybrid approach is its enhanced convergence speed, achieved through the reduction of search space dimensions compared to the standard backpropagation method in neural networks.

Table 1
Forward and backward pass for ANFIS.

	Premise parameters	Consequent parameters	Signals
Forward pass	Fixed	Least-Squares estimator	Node outputs
Backward pass	Gradient decent	Fixed	Error signals

The final output can be represented as a linear combination of the consequent parameters. The error function used to train ANFIS is defined as follows [33]:

$$E = \sum_{k=1}^{n}(f_k - f_k')^2 \tag{5}$$

where f and f_k' are the kth desired and estimated output, respectively, and n represents the total number of input-output pairs in the training set.

The ANFIS architecture consists of five layers, as depicted in Fig 2 [3]. The adaptive nodes represented by square nodes have parameters that are updated during training, while the fixed nodes represented by circular nodes have parameters that remain constant throughout training.

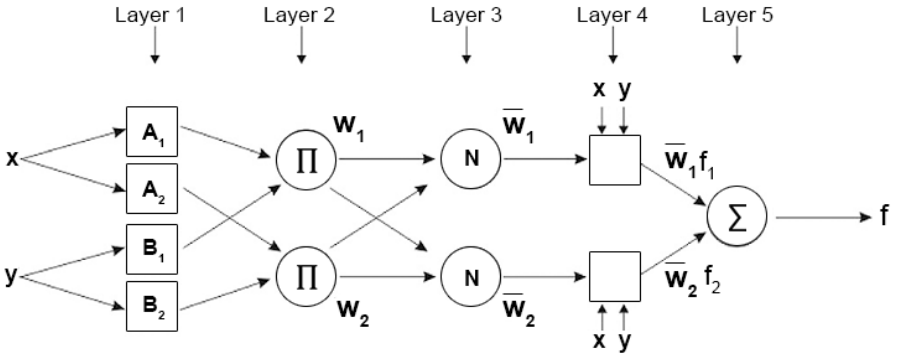

Fig. 2. ANFIS architecture and layers [3].

The first layer generates membership values for each of the fuzzy sets using membership functions, where x and y represent the non-fuzzy inputs to the i^{th} node.

$$O_{1,i} = \mu_{Ai}(x) \quad i = 1,2 \tag{6}$$

$$O_{1,i} = \mu_{B(i-2)}(x) \quad i = 3,4 \tag{7}$$

where $O_{1,i}$ is the output of the i node of the first layer. μ_{Ai} and μ_{Bi} are appropriate membership functions with linguistic labels A_i and B_i, respectively.

The second layer contains nodes labeled Π, which output the product of all incoming signals. The output of each node indicates the firing strength of a rule, which represents the extent to which the antecedent part of a fuzzy rule is satisfied and determines the shape of the output function of that rule.

$$O_{2,i} = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y) \quad i = 1,2 \tag{8}$$

where $O_{2,i}$ is the output of the i node of the second layer. w_i is firing strength of the i^{th} rule.

The third layer consists of fixed nodes labeled N, and its outputs are referred to as normalized firing strengths.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2} \tag{9}$$

where $o_{3,i}$ is the output of the third layer. $\overline{w}_i$ is the normalized firing strength.

The fourth layer computes the contribution of the i^{th} rule to the output using an adaptive function, and its nodes are adaptive nodes.

$$O_{4,i} = \overline{w}_i\, f_i = \overline{w}_i(\, p_i\, x + \, q_i\, y + \, r_i) \tag{10}$$

where $O_{4,i}$ is the output of the fourth layer. f_i is the linear function of the input. p_i, q_i and r_i are the consequent parameters.

The fifth layer contains a node labeled Σ, which computes the sum of all input signals.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{11}$$

where $O_{5,i}$ is the output of the fifth layer.

To develop the ANFIS model for predicting swelling percentage, the process involved creating a FIS using a specific set of training data. This FIS was then subjected to training and validation through ANFIS. Finally, the performance of the model was assessed using a separate testing subset. The study employed subtractive clustering and FCM clustering techniques to create the initial FIS for the models.

By introducing the ANFIS theory, it is beneficial to link these concepts more explicitly to the specific problem of predicting soil swelling. So, here it just mentioning to some examples of the ANFIS modelling predicting and the soil parameters field. An ANFIS is used by Mikaeil et al. [34] to estimate the wear rate of a diamond wire saw in dimension stone quarries. By employing subtractive clustering method and FCM clustering method, the ANFIS model incorporates important rock properties to indirectly predict the wear rate with high accuracy. This offers a promising alternative to existing models in assessing factors that affect the diamond wire saw's wear rate. Keshavarz and Torkian [5] examines the application of soft computing methods like ANN and ANFIS to predict concrete's compressive strength. Through experiments on various concrete specimens, it is found that both ANN and ANFIS models are effective in predicting compressive strength, with ANFIS demonstrating superior performance compared to ANN. Jangir and Satavalekar [28] used MATLAB's Fuzzy Tool ANFIS to predict soil liquefaction potential and settlements. Separate ANFIS models, LP-ANFIS and LIS-ANFIS, were developed using Cone Penetration Test (CPT) data. The models showed strong correlation, indicating the effectiveness of ANFIS in determining liquefaction potential and settlements based on CPT data.

3. Database

The database used to develop ANSIS models comprises 58 sets of data obtained from 58 different soil tests conducted by Erzin and Güneş [35] using the ASTM D4546 [36]

Consolidometer for swelling tests. Fig 3 shows a schematic diagram of the Consolidometer and the characteristics of the soil samples used in the swelling tests. In this test, the soil sample is placed between two porous stones and completely submerged in water, and a displacement gauge is placed on top of the sample to measure the variation in sample height. Since the lateral sides of the sample are confined by a rigid ring, the sample swells only in the vertical direction. The height increase is measured by the top gauge, and the value read at the end of the test is the free swelling of the sample (ΔH). The ratio of the increase in height (ΔH) to the initial height of the sample (H) is referred to as the swell percentage, $S=\frac{\Delta H}{H}$.

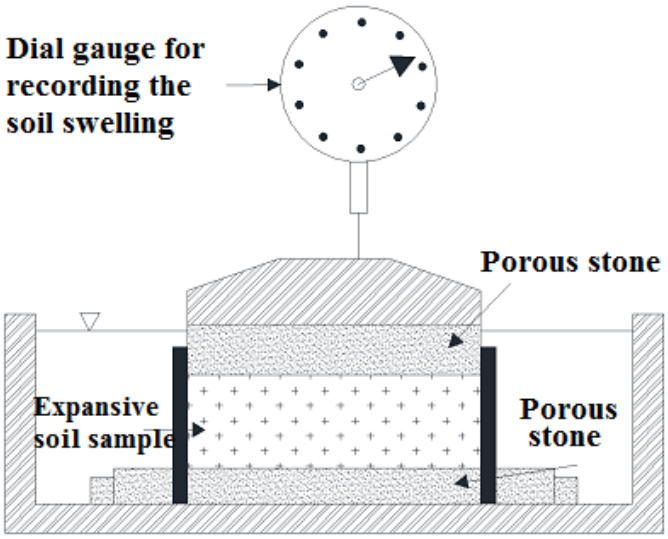

Fig. 3. Consolidometer.

The soil samples used in the tests are mixtures of clay that contain varying percentages of kaolinite and bentonite. Table 2 provides information on the commercial characteristics of these two clay minerals, including specific gravity (Gs), clay content (C, %), liquid limit (LL, %), plastic limit (PL, %), plasticity index (PI, %), and cation exchange capacity (CEC, meq/100g).

Table 2
Characteristics of Kaolinite and Bentonite clay minerals.

Material	Gs	C (%)	LL (%)	PL (%)	PI (%)	CEC (meq/100g)
Kaolinite	2.66	49	37	22	15	12
Bentonite	2.78	78	472	96	376	86

Various initial moisture contents were used to statically compact these soil samples, and their properties were measured, including clay percentage (C), cation exchange capacity (CEC meq/100g), plasticity index (PI %), initial water content (w %), initial dry unit weight (γ_{dry} kN/m^3), and swell percentage (S %), the data was divided into three subsets: a training dataset for model training, a validation dataset to prevent overfitting during the training process, and a testing dataset to evaluate the predictive ability of the model. The data was split into percentages of 60 % for training, 20 % for validation, and 20 % for testing.

4. Result and discussion

4.1. Model creation and training

To develop ANFIS predictive models, an initial FIS must be created first, and then the FIS model should be trained using ANFIS. There are various methods available to create a FIS, such as: a) Using the GUIs of the Fuzzy Logic Toolbox and b) Writing code and using the commands available in the MATLAB library. In this study, due to the limitations, the GUIs were not used, and a program was written specifically for this purpose. Some of the limitations of the GUIs are as follows:

The maximum number of overall membership functions for the GUIs is 15. For the modeling done for the swell percentage, which has 5 inputs, a maximum of 3 membership functions must be determined for each input, resulting in a total of 15 membership functions (or any other combination that does not exceed 15 membership functions). With this number of membership functions, it is not possible to achieve sufficient accuracy. If the number of membership functions is more than 15, the program displays the "out of MATLAB memory" error, which will result in a several-fold increase in the program's execution time and a higher probability of error. Therefore, using coding in the MATLAB software environment, it is possible to create a greater number of membership functions without any limitations and solve the problem with an acceptable degree of accuracy.

This study developed two ANFIS models, named FIS1S and FIS2S, to predict the swelling percentage of soils. The initial FIS structure of FIS1S is subtractive clustering, while that of FIS2S is FCM clustering. The inputs for both models include clay percentage (C %), cation exchange capacity (CEC meg/100g), plasticity index (PI %), initial water content (w %), and initial dry unit weight (γ_{dry} kN/m^3), while the output is swelling percentage (S %). Also, in the first step of modeling, the relationship between the accuracy of problem-solving and the number of membership functions must be determined to achieve the optimal solution. The following sections present the construction of two prediction models, FIS1S and FIS2S, along with their respective outcomes and corresponding discussions.

4.2. Model FIS1S using subtractive clustering

Subtractive clustering is an algorithm that quickly determines the optimal number of data clusters for a desired range of influence. Each data point is assigned a potential based on its location relative to all other data points. The data point with the highest potential is chosen as the first cluster center. Next, the potential is recalculated for all other points, excluding the influence of the first cluster center, to obtain the other clusters. The clustering process continues until all cluster centers have been defined. Each cluster center represents a fuzzy rule that describes the system behavior in terms of the distance to the defined cluster centers [37,38]. To determine the optimal influence radius for the FIS1S model using subtractive clustering, a program was created in MATLAB software as part of this research. The flowchart of the program is presented in Fig 4.

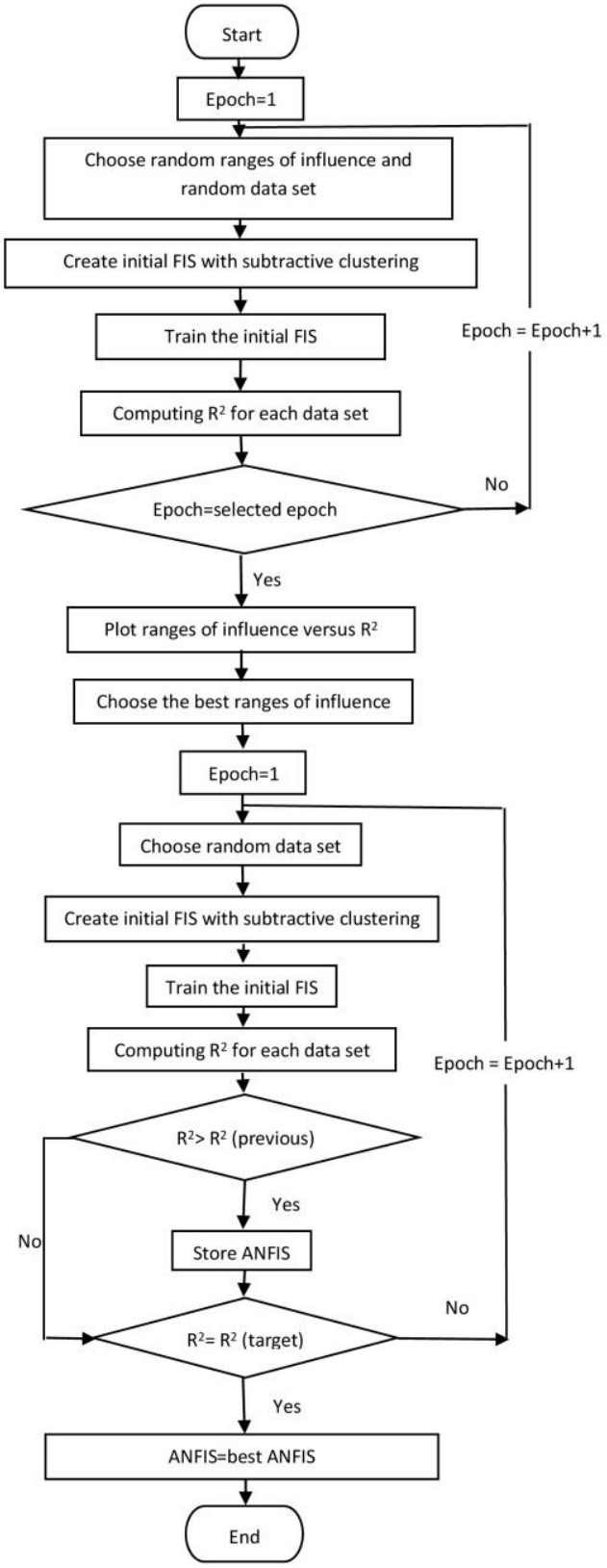

Fig. 4. The flowchart of the program developed to determine the optimized range of influence for the FIS1S model using subtractive clustering.

Fig 5 depicts the results obtained from the program, showing how the prediction ability of the FIS1S model, as indicated by R^2, varies with changes in the range of influence. According to Fig 5, the FIS1S model achieved high R^2 values when the range of influence was between 0.3 and 0.9. Increasing the range of influence led to the formation of more cluster centers, resulting in shorter training times for the program. Therefore, a larger value for the range of influence was selected. For the FIS1S model, the range of influence was chosen to be between 0.95 and 1.3. The program was then re-executed within this range to achieve the best accuracy. The highest R^2 value for the FIS1S model was obtained at a range of influence of 1.1.

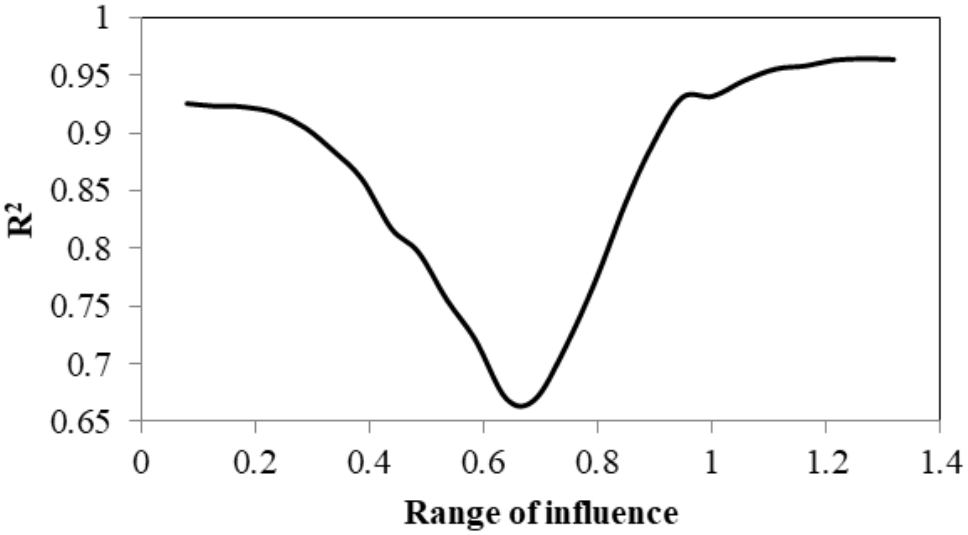

Fig. 5. The impact of the range of influence on the predictive capability of the FIS1S model.

4.3. Model FIS2S using FCM clustering

The FCM algorithm establishes a relationship between each data point and a cluster center based on the data matrix, for a desired number of cluster centers. The degree of membership of a data point is represented by its degree of belonging to a cluster. The number of membership functions [39] and rules is equivalent to the number of cluster centers. To determine the optimal number of cluster centers in FCM clustering for the FIS2S model, another program was developed using MATLAB software in this study. The flowchart of the program is depicted in Fig 6.

Fig 7 shows the results obtained from the program, depicting how the predictive capability of the FIS2S model, as indicated by R^2, varies with changes in the number of cluster centers. According to Fig 7, the highest R^2 range is achieved with 3 to 8 cluster centers. Therefore, the program was executed within this range and the optimal number of cluster centers for the FIS2S model was determined to be 7. The membership functions for the FIS1S and FIS2S models before and after training are shown in Fig 8 and Fig 9, respectively. The characteristics of the FIS1S and FIS2S models are presented in Table 3.

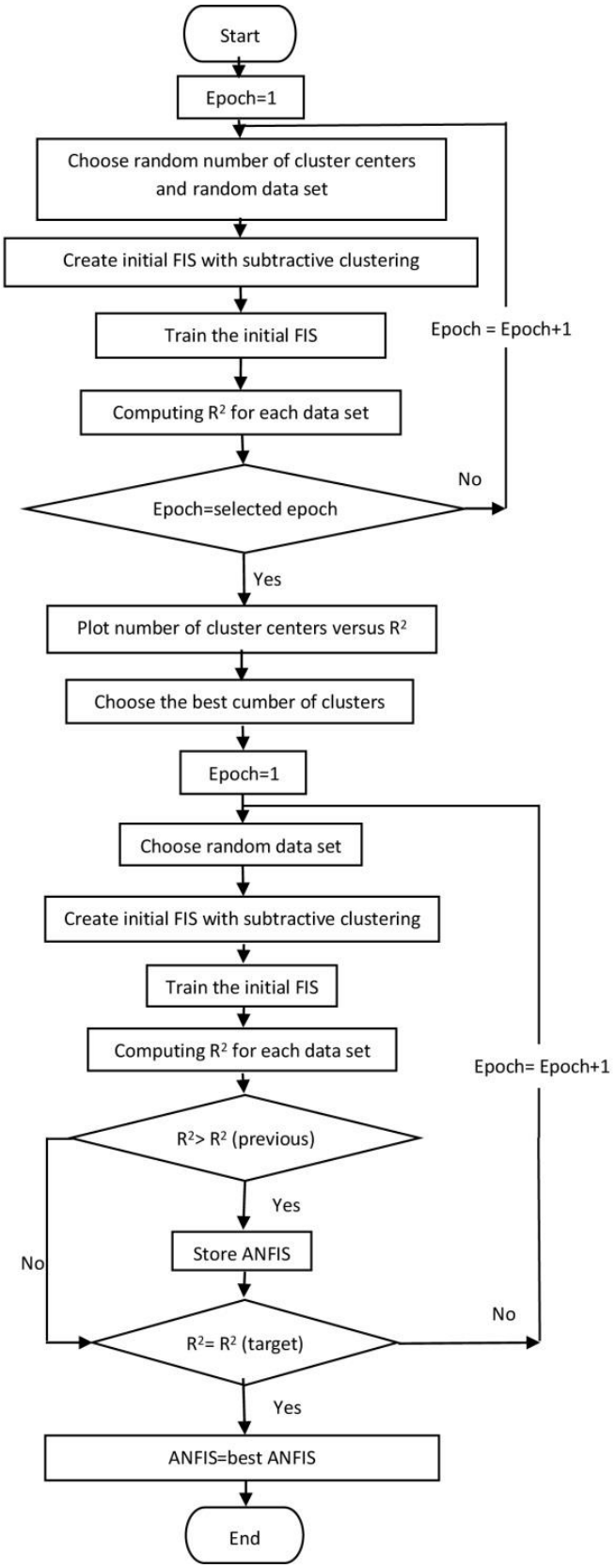

Fig. 6. The flowchart of the program developed to determine the optimal number of cluster centers for the FIS2S model using FCM clustering.

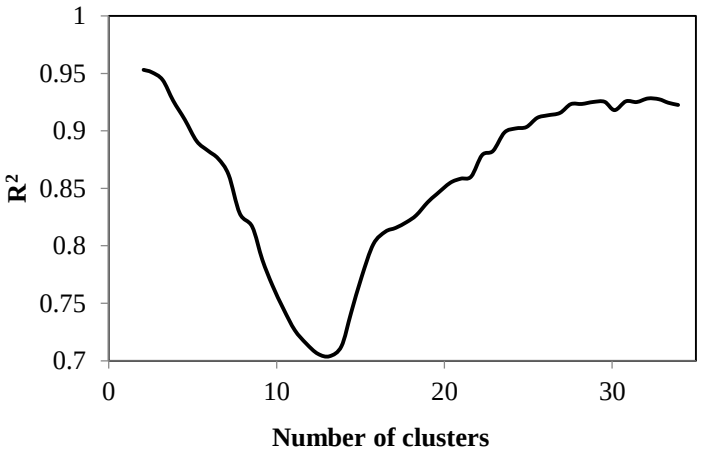

Fig. 7. Effect of number of cluster centers on prediction ability of FIS2S model.

Table 3
The optimized FIS1S and FIS2S models for swelling percentage.

Model	FIS1S	FIS2S
Type	Sugeno	Sugeno
Input membership function type	Gauss function	Gauss function
Output membership function type	Linear	Linear
Number of membership functions and rules	3	7
And method	Prod	Prod
Defuzzification method	Weighted average	Weighted average

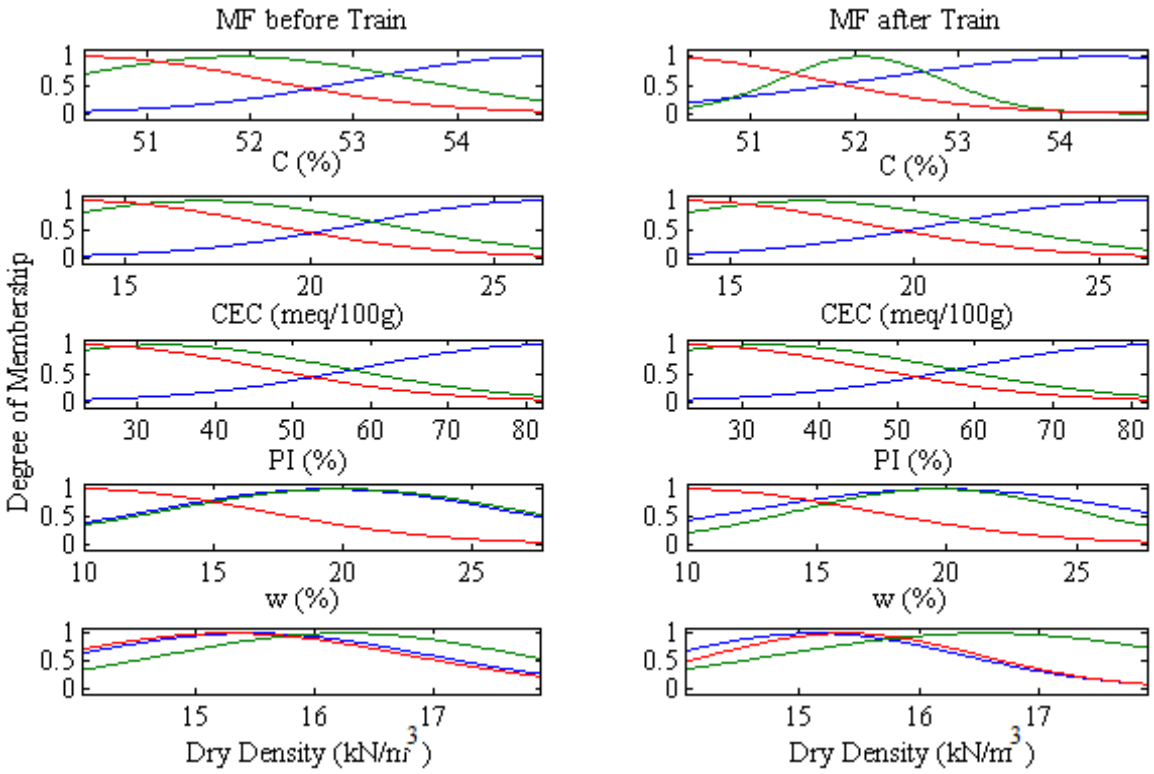

Fig. 8. The membership functions for the FIS1S model before and after training.

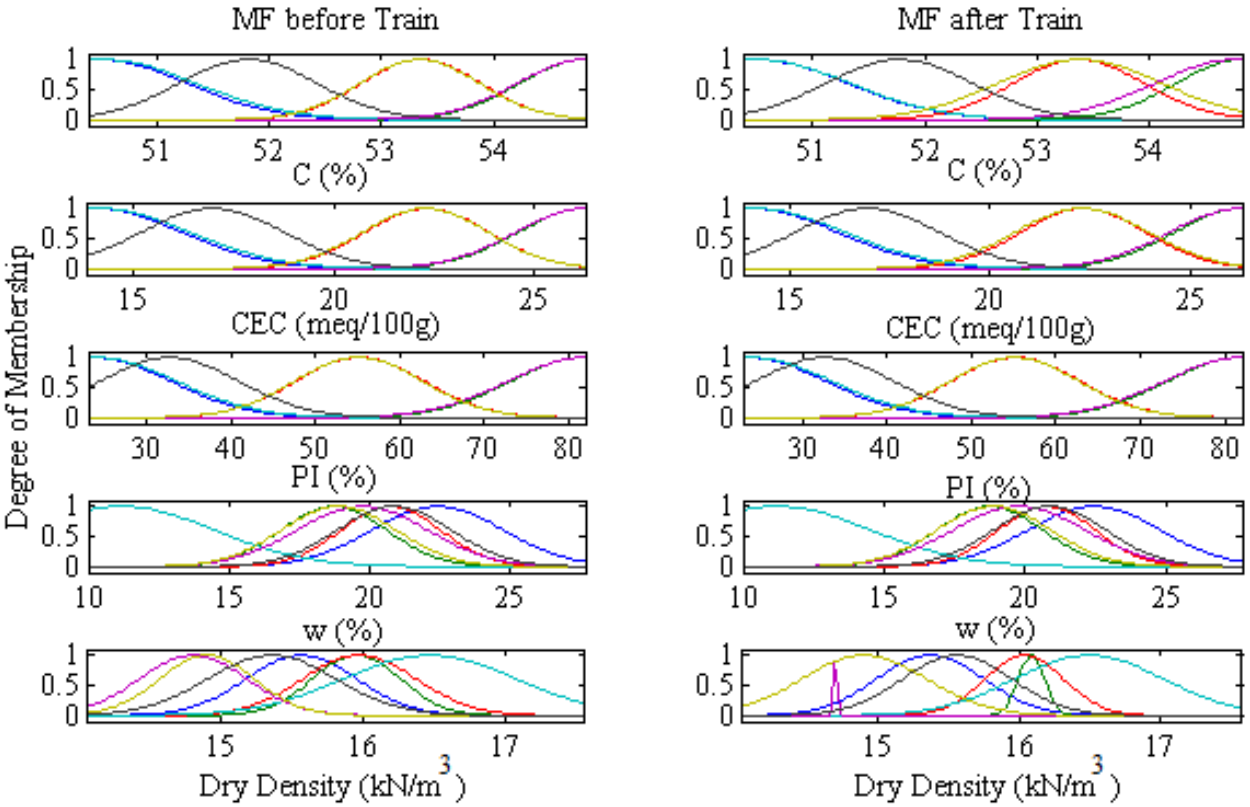

Fig. 9. The membership functions for the FIS2S model before and after training.

4.4. Model testing

Once the training process was completed, the accuracy and predictive capability of the models were evaluated. To do so, the trained FIS1S and FIS2S models were each presented with a series of training, check, and test datasets. For each dataset, the ANFIS predicted values were compared to the measured values, and the coefficient of determination R^2 was computed. The results are depicted in Fig 10 and Fig 11, and summarized in Table 4. Based on these figures, the coefficient of determination for the test data was found to be 0.996 for the FIS1S model and 0.984 for the FIS2S model, indicating that both models have high predictive capabilities. Other performance measures, including VAF (variance account for), MAE (Mean Absolute Error), and RMSE (Root Mean Square Error) [3], were calculated for both the FIS1S and FIS2S models. The results are shown in Table 4. Additionally, Table 4 also presents the swelling percentage forecasts obtained through ANN modeling conducted by Erzin and Güneş [35]. It is evident that the modeling results using ANFIS have yielded comparatively better outcomes. Table 4 shows that the coefficient of determination R^2 for predicting test data is 0.99 for the FIS1S model and 0.98 for the FIS2S model, demonstrating their high generalization ability. The VAF values for both ANFIS models are close to 100, with 99.28 for the FIS1S model and 98.32 for the FIS2S model, indicating excellent performance. These results suggest that both programs developed in this study were able to successfully optimize the subtractive clustering and FCM clustering models to achieve the highest predictive capabilities.

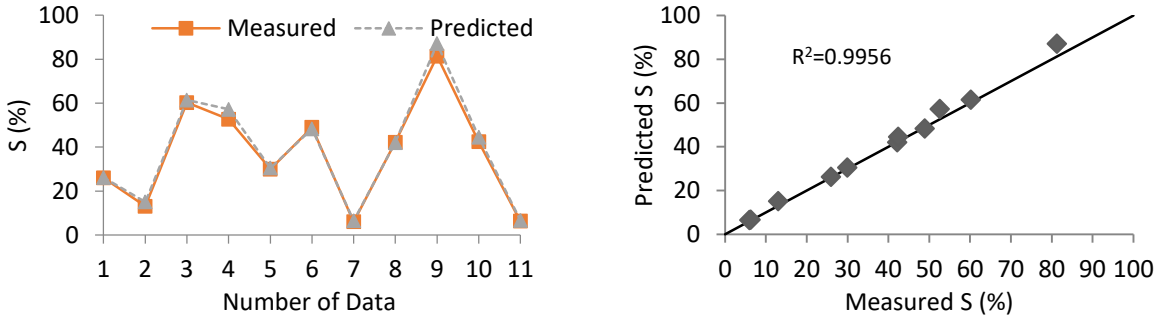

Fig. 10. The assessment of the predictive capability of the FIS1S model for the test data.

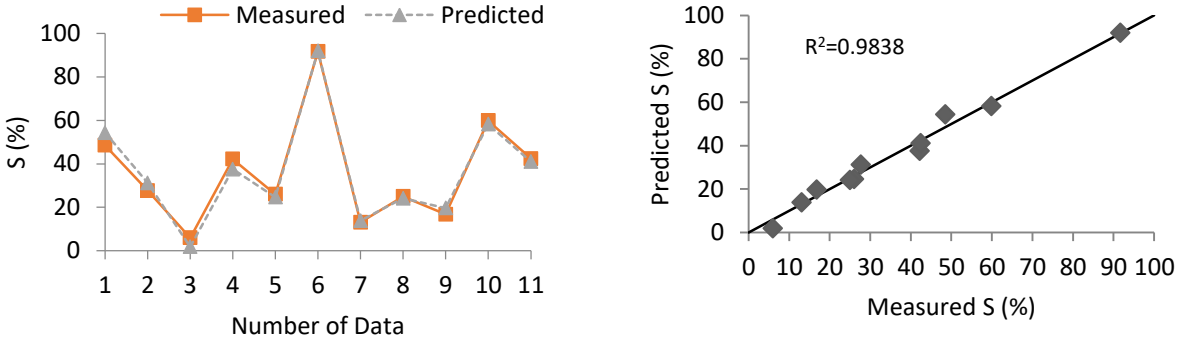

Fig. 11. The assessment of the predictive capability of the FIS2S model for the test data.

Table 4
performance of ANFIS models.

Performance Index	Data set	ANFIS Models		Erzin and Güneş [35] models
		FIS1S	FIS2S	ANN
R^2	Testing	0.9956	0.9838	0.9652
RMSE (%)	Testing	2.4197	3.0269	5.15
MAE (%)	Testing	1.6173	2.4736	3.82
VAF (%)	Testing	99.2774	98.3168	96.16

Hence, it can be inferred that artificial intelligence predictive models can be effectively employed to predictive Civil Engineering parameters with satisfactory accuracy and reliable performance. So, utilizing the approach outlined in this research, ANFIS models are constructed by training them with the most suitable number of cluster centers. Subsequently, by inputting information into the model, the corresponding output can be determined.

5. Sensitivity analysis

To assess the impact of the inputs on the model output, sensitivity analysis was conducted using the cosine amplitude method [11,40]. To apply this method, all data pairs were represented in a common X-space. The data pairs were used to construct a data array X, defined as:

$$X = \{x_1, x_2, x_3 , \dots . x_i, \dots x_n\} \quad (12)$$

Each element x_i in the data array X is a vector with a length of m, where x_i is:

$$x_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}\} \tag{13}$$

Therefore, each dataset can be viewed as a point in an m-dimensional space, where m coordinates are required to fully describe each point. Each point in space is related to results in a pairwise comparison. The strength of the relationship between the datasets x_i and x_j is represented by r_{ij}, as defined by equation 14:

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}} \tag{14}$$

Fig 12 clearly demonstrates that PI holds the highest influence on soil swelling in both the FIS1S and FIS2S models. This suggests that variations in the PI value have a substantial impact on the model's ability to predict soil swelling percentage accurately. Notably, the analysis of the figures reveals that each input parameter, namely C, CEC, PI, ω, and γ_{dry}, exhibits a significant effect on the model output. Consequently, this implies that all the selected input parameters were appropriate choices for the FIS1S and FIS2S models. By considering the diverse range of inputs and their substantial influence on the model outputs, a comprehensive and reliable prediction of soil swelling percentage can be achieved. These findings provide sound evidence for the robustness and effectiveness of the FIS1S and FIS2S models in capturing the intricacies of soil behavior and accurately projecting swelling phenomena.

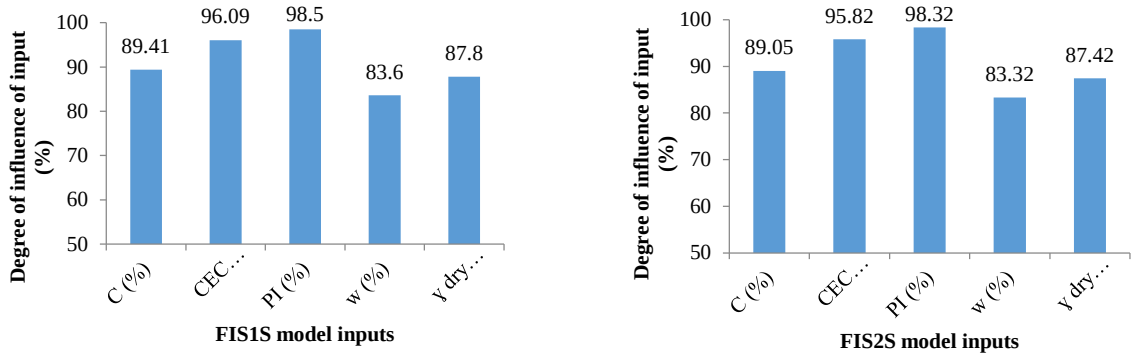

Fig. 12. The results of the sensitivity analysis conducted for soil swelling in the FIS1S and FIS2S models.

6. Conclusions and suggestions

This study successfully optimized the subtractive clustering and FCM Clustering ANFIS models for predicting the swelling of expansive soils. Initially, two ANFIS models were developed for swelling prediction: the FIS1S model using subtractive clustering and the FIS2S model using FCM structure. Subsequently, two MATLAB programs were developed to optimize these models. The following are some of the results obtained:

- One notable achievement of this study is the determination of the optimal number of membership functions for predicting swelling percentage. By utilizing coding techniques

without restrictions on the number of membership functions, a fine balance between prediction accuracy and problem-solving time was achieved. The identification of the most optimal number of membership functions is a significant contribution to the field.

- The developed programs also contributed to the optimized performance of the models. The first program successfully determined the optimal influence radius for the FIS1S model, while the second program optimized the number of cluster centers for the FIS2S model, thus maximizing their predictive capabilities. The results demonstrated the exceptional performance of both the FIS1S and FIS2S models in achieving their highest predictive ability.
- Furthermore, sensitivity analysis using the cosine amplitude method was conducted to assess the impact of inputs on swelling percentage in the ANFIS models. The results highlighted the significant effect of inputs on swelling percentage in both the FIS1S and FIS2S models. This understanding provides valuable insights into the factors influencing swelling behavior in expansive soils.
- With the excellent performance of the developed programs and the comprehensive insights obtained from the sensitivity analysis, there is immense potential for their application in optimizing subtractive clustering and FCM clustering models for accurately modeling other engineering aspects. This research opens up new avenues for the effective utilization of ANFIS models in various engineering domains, contributing to enhanced predictions and decision-making processes.

In order to enhance accuracy and reduce problem-solving time, the suggestion in the paper is to utilize ANFIS for predicting civil engineering parameters. These parameters typically necessitate extensive and intricate testing. The approach involves leveraging valid and accessible data while employing subtractive clustering and FCM clustering techniques with an optimal number of clustering centers. This methodology aims to facilitate the creation of the initial FIS and subsequent model training by ANFIS.

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Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

MHJ, AH: Conceptualization; MHJ: Data curation; MHJ: Formal analysis; MHJ, AH: Investigation; MHJ, AH: Methodology; MHJ: Project administration; MHJ: Resources; MHJ: Software; AH: Supervision; MHJ, AH: Validation; MHJ: Visualization; MHJ: Roles/Writing – original draft; MHJ, AH: Writing – review & editing.

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